

Partitioning uncertainty in streamflow projections under nonstationary model conditions

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ABSTRACT

Assessing the impacts of Land Use (LU) and climate change on future streamflow projections is necessary for efficient management of water resources. However, model projections are burdened with significant uncertainty arising from various sources. Most of the previous studies have considered climate models and scenarios as major sources of uncertainty, but uncertainties introduced by land use change and hydrologic model assumptions are rarely investigated. In this paper an attempt is made to segregate the contribution from (i) general circulation models (GCMs), (ii) emission scenarios, (iii) land use scenarios, (iv) stationarity assumption of the hydrologic model, and (v) internal variability of the processes, to overall uncertainty in streamflow projections using analysis of variance (ANOVA) approach. Generally, most of the impact assessment studies are carried out with unchanging hydrologic model parameters in future. It is, however, necessary to address the nonstationarity in model parameters with changing land use and climate. In this paper, a regression based methodology is presented to obtain the hydrologic model parameters with changing land use and climate scenarios in future. The Upper Ganga Basin (UGB) in India is used as a case study to demonstrate the methodology. The semi-distributed Variable Infiltration Capacity (VIC) model is set-up over the basin, under nonstationary conditions. Results indicate that model parameters vary with time, thereby invalidating the often-used assumption of model stationarity. The streamflow in UGB under the nonstationary model condition is found to reduce in future. The flows are also found to be sensitive to changes in land use. Segregation results suggest that model stationarity assumption and GCMs along with their interactions with emission scenarios, act as dominant sources of uncertainty. This paper provides a generalized framework for hydrologists to examine stationarity assumption of models before considering them for future streamflow projections and segregate the contribution of various sources to the uncertainty.

1. Introduction

Projecting the hydrologic impacts of Land Use (LU) and climate change is necessary for developing adaptive water resources management policies. Hydrologic models are most widely used tools for performing impact assessment studies. Using a hydrologic model for such studies involves calibrating the model, by optimizing the model parameters to match the model simulations with observed records. Usually, a single split sample technique is followed where the model is calibrated for a particular time slice and then validated over another time slice (Li et al., 2012). This process is based on the implicit assumption of hydrologic model stationarity in which the calibrated model parameters are assumed to be time invariant (Milly et al., 2008). Assessing the applicability of this assumption is necessary to ensure the transferability of the model to future time periods. Recently, temporal

variability of the hydrologic model parameters is also addressed in model calibration. Merz et al. (2011) evaluated time stability of model parameters by calibrating the model for 6 consecutive 5-year periods and concluded that the impact of assuming model parameters to be stationary on model output can be significant. Li et al. (2012) assessed the transferability of hydrologic models by splitting the data into 120 time windows over 4 climatic periods. They observed that the model calibrated under one set of the climatic condition is transferable only to time periods having similar climatic conditions. From the literature, it is clear that the assumption of stationarity may not be valid for all the cases and caution should be exercised while transferring a model to future conditions. Hereafter, nonstationarity of hydrologic model parameters will be referred to as nonstationarity of the hydrologic model for simplicity.

Further, impact assessment studies involve a cascade of uncertainty

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sources such as LU projections, climate models and scenarios, model assumptions along with inherent variability of the system (Bastola et al., 2011; Bosshard et al., 2013) that contribute significantly to the uncertainty in streamflow projections. Performing hydrologic impact analysis within the uncertainty framework is essential for quantifying future water availability (Beven, 2002; Wheater and Gober, 2013). Numerous studies in the past used a combination of aforementioned sources with an attempt to reduce uncertainty in streamflow simulations, but segregating the contribution of individual sources to uncertainty in hydrologic projections is rarely considered. The factors mentioned earlier (i.e., LU projections, climate models, model assumptions and internal variability of the system) in general, do not contribute equally to the uncertainty in streamflow projections. It is, therefore, necessary to segregate their individual contribution to gain insight into the importance of each source. In this regard, a few studies deal with uncertainty contribution from various sources (Jung et al., 2011; Addor et al., 2014; Exbrayat et al., 2014; Hingray and Said, 2014; Mockler et al., 2016; Parajka et al., 2016; and Whateley and Brown, 2016). Wilby and Harris (2006) quantified uncertainty from General Circulation Models (GCMs), emission scenarios, downscaling, hydrologic model parameters and model structure within the probabilistic framework and observed that GCMs and downscaling technique are significant sources of uncertainty to changes in low flow regime of Thames River. Bosshard et al. (2013) used a combination of 8 climate models, 2 post-processing techniques and 2 hydrologic models to quantify uncertainty from these sources on hydrologic projections in Alpine Rhine and reached a similar conclusion that the climate models are the dominant source of uncertainty. More recently, the work of Mockler et al. (2016) assessed the importance of rainfall and model parameters along with their interactions on hydrologic model simulations. They found that rainfall along with the choice of hydrologic model has a significant contribution to the uncertainty.

None of the studies conducted earlier consider simultaneously nonstationarity in the hydrologic model and LU change as the source of uncertainty in streamflow projections. With this background, this study aims at decomposing the streamflow uncertainty into the contribution from various sources under nonstationary model conditions. Specifically, three objectives are undertaken in this study: (1) investigating the effect of nonstationary model parameters in the hydrologic model; (2) assessing the difference in hydrologic impacts of future LU and climate scenarios under nonstationary and stationary model conditions; and (3) segregating the contribution of different sources to the uncertainty. For exploring nonstationarity in the hydrologic model, a multiple-split sample approach is used. The contribution of different sources to the uncertainty in model output (projected streamflow) is quantified using the ANalysis of VAriance (ANOVA) approach. It is to be noted that, variance or spread in the projections is referred to as uncertainty in this paper. Uncertainty sources considered are (i) GCMs, (ii) emission scenarios (Sce), (iii) LU, (iv) hydrologic model parameters (MP) – assumed to be stationary or nonstationary, and (v) and internal variability (IV) of the system. Fig. 1 presents the framework of the methodology followed in this paper.

Upper Ganga Basin (UGB), located in northern India is selected as the study region for analysis (Fig. 2). Ganga basin is densely populated (44% of India's population according to the census report, 2011) and is of great socio-economic importance to India. It occupies 30% of India's cropland area.

Uncertainty assessment in the present work is carried out by employing a semi-distributed Variable Infiltration Capacity (VIC) hydrologic model (Liang et al., 1994). A key feature of the VIC model lies in its ability to represent land surface in the form of grids, where the size of each grid can vary from $1/8^\circ$ to 2° . Each grid can have multiple soil layers, but typically 3 layers are considered. Within a VIC model grid, heterogeneity in vegetation is represented in the form of tiles. Owing to the difference in the land surface properties, each tile generates varying response to the input precipitation through infiltration, soil moisture

storage, evapotranspiration, and runoff. For each grid, water balance equation is solved to obtain different components of the hydrologic cycle. A complete description of the VIC model is provided in detail by Liang et al. (1994), Liang et al. (1996) and Nijssen et al. (1997). Once VIC concludes the computation of water balance for each grid within the watershed, streamflow is simulated by employing a separate routing model (Lohmann et al., 1996; 1998a; b). The following section describes data used followed by the description of the methodology employed in this work.

2. Data and methods

2.1. Study area and observed data

The study region Upper Ganga Basin (UGB) in India spans $25^\circ 30'N$ – $31^\circ 30'N$ in latitude and $77^\circ 30'E$ – $80^\circ E$ in longitude with an approximate area of $96,000 \text{ km}^2$ (Fig. 2). Topographic information of the region is obtained data from ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) DEM (Digital Elevation Model), available at 30 m spatial resolution. Significant variation in the topographic profile of the region can be observed from upstream to downstream reaches of the UGB (Fig. 2). Based on the distinct topography and LU, the UGB is divided into three sub-basins (Fig. 2): upstream (from the upstream most point of the basin till Bhimgodha outlet, covering 24% of the UGB); midstream (from Bhimgodha to Ankinghat outlet, 63% of the UGB), and downstream (from Ankinghat to the basin outlet at Allahabad, covering 13% of the UGB). Further details pertaining to the study area are described elaborately by Chawla and Mujumdar (2015). The diversity in the physiography and climatology of the region makes this as an interesting case study to pursue in the current context.

Observed or historic rainfall, maximum temperature and minimum temperature for the present study is acquired from Indian Meteorological Department (Rajeevan et al., 2006) and wind speed is procured from Princeton University (Sheffield et al., 2006). Climate data from both the sources are brought to a common resolution of 0.5° , which is also the scale at which the VIC model is executed in the present work. Observed streamflow data is obtained from Uttar Pradesh Irrigation Department and Central Water Commission (CWC). The observed streamflow in the UGB is available for two locations: (a) Bhimgodha (1987–2011), and (b) Ankinghat (1977–2009) (Fig. 2) at monthly scale. The VIC model calibration and validation is carried out at these locations. However, between Bhimgodha and Ankinghat, several control structures are located [Fig. 2(b)]. The effect of these control structures is taken into account by converting the observed (regulated) flow to naturalized flow, considering the outflow from the Bhimgodha barrage and the discharges in the canals. The data of Bhimgodha barrage operations and the discharges in the canals were procured from the CWC. The naturalized flow data thus obtained is used for model calibration and validation. Soil dataset used in this study is obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP).

2.2. Future land use and climate projections

Land Use (LU) is considered as a major driver of change in water resources (Vörösmarty et al., 2000; DeFries and Eshleman, 2004; Oki and Kanae, 2006). Therefore, modeling spatio-temporal changes in the LU pattern of a region and understanding its implication on hydrologic processes have drawn significant attention in the recent decade (Buytaert et al., 2007; Randhir and Tsvetkova, 2011; Wilson and Weng, 2011; Öztürk et al., 2013). In order to assess future estimates of water resources in a region, future projections of LU are required, which serve as key input for the hydrologic model.

A wide range of spatially explicit LU models are available to obtain future LU projections of a region, a review of which is presented in

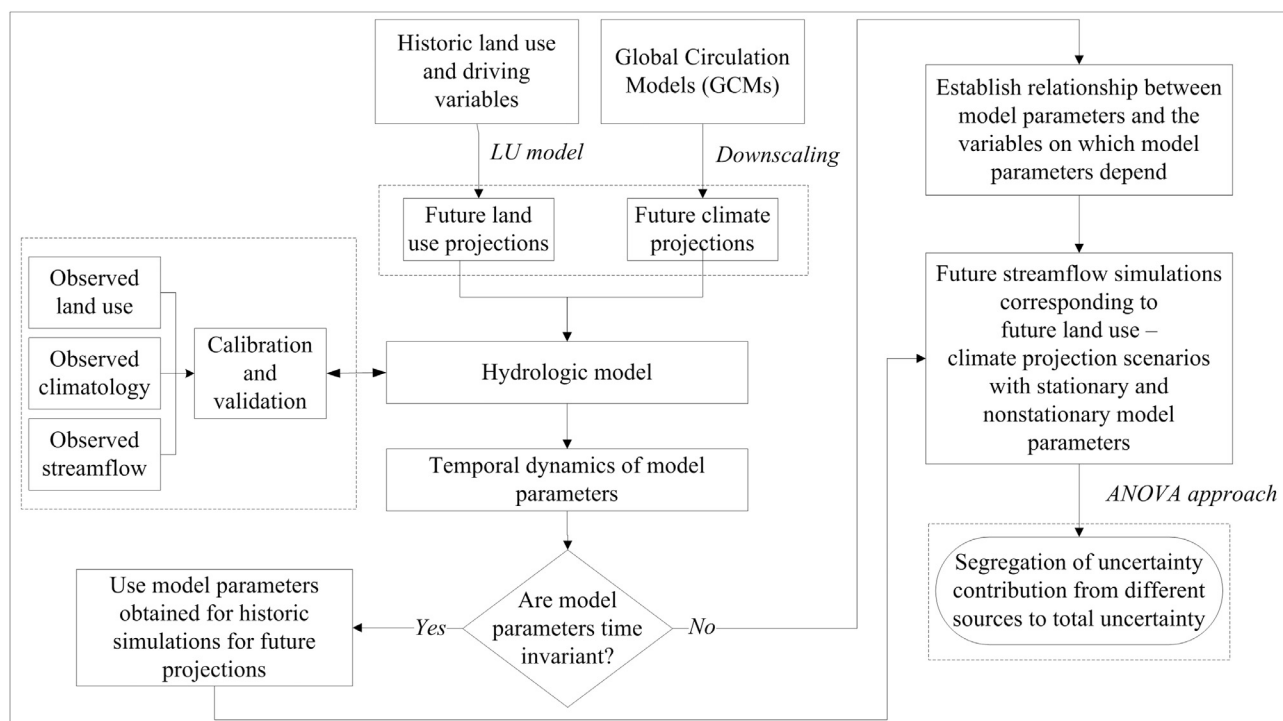


Fig. 1. Framework for quantification and segregation of uncertainty in streamflow projections.

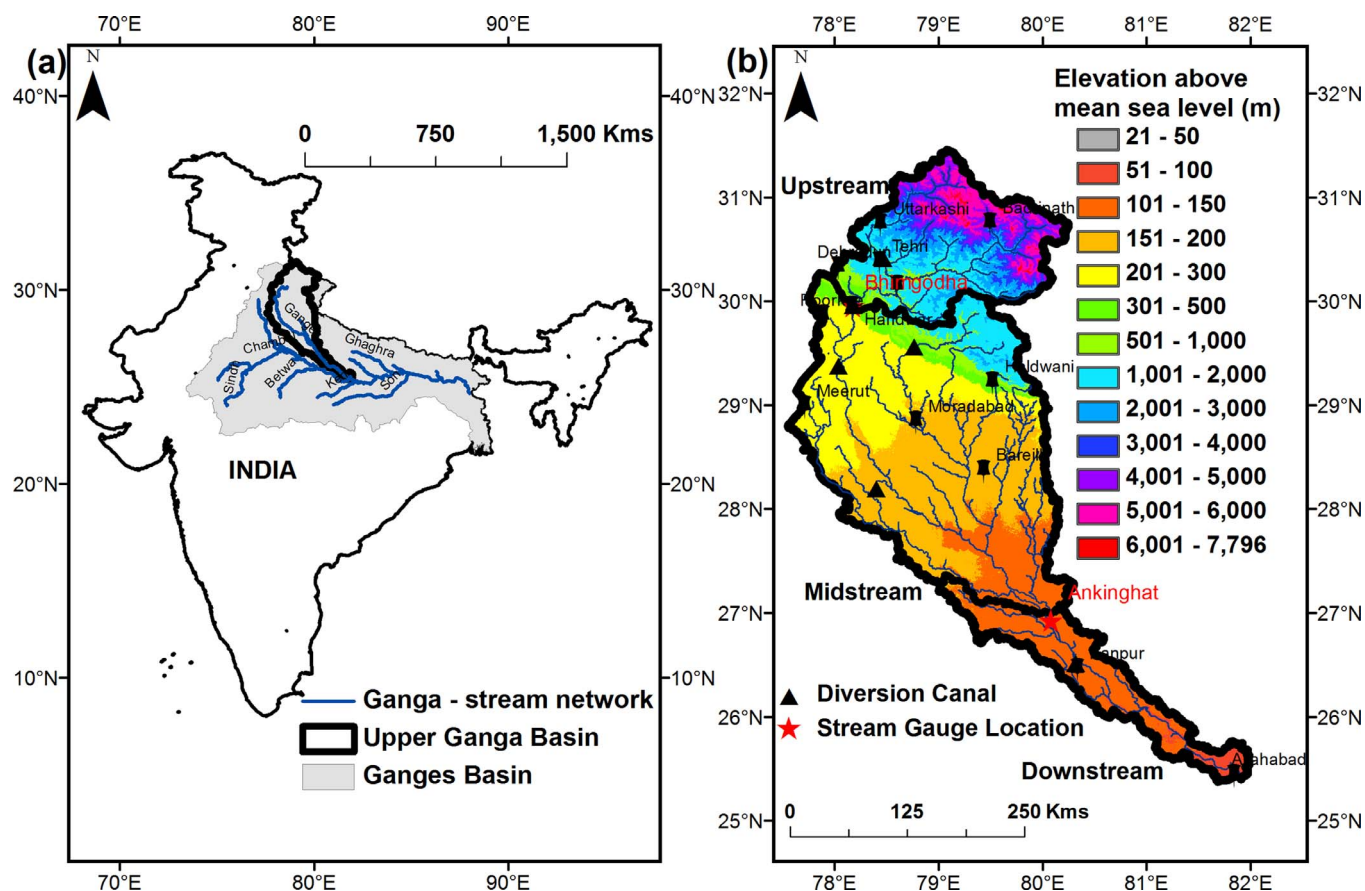


Fig. 2. (a) Location of Upper Ganga Basin (UGB) within Ganges Basin in India; (b) Details of the UGB.

Verburg et al. (2004) and Mas et al. (2014). These models perform change projection by empirically relating the transitions of interests with driving variables of LU change (Mas et al., 2014). Spatial distance between these variables and the target layer (comprising of pixels being mapped for change in future) is calculated and considered as an input data for LU change modeling.

In this paper, a neural network based LU model is considered for projecting LU into the future. To achieve this, digitized network of roads, streams, urban areas, elevation, and slope are considered as driving variables. Output layer comprises of temporal transitions (such as forest to crop land or barren land to the urban area) to be modeled. Further details related to LU modeling (using the neural network), which are beyond the scope of this paper, can be obtained from Atkinson & Tatnall (1997) and Eastman (2009).

The process of projecting LU into the future is carried out in two stages: in the first stage, observed LU maps for the years 1980 and 2000 are used to simulate LU for the year 2011. Observed LU maps for the region are created using the Landsat imageries, results and accuracy are provided by Chawla and Mujumdar (2015). Simulated LU map of 2011 is compared with the observed map of 2011 for determining the potential errors. This exercise acts as validation, to assess the ability of the LU model to appropriately predict changes using the considered set of drivers. Further details pertaining to validation of the LU model are provided in Appendix A. The model was found to replicate the spatial pattern of LU of the year 2011 with a reasonable accuracy. Areas under different LU categories are also found to be close to each other in the two images (Appendix A, Table A.1).

Post validation, LU maps of 2000 and 2011 are used to predict LU for the year 2020. Further, using the observed map of 2011 and predicted map of 2020, LU is projected for 2030. The same process is repeated using the maps to 2020 and 2030 to obtain LU for the year 2040. Due to uncertainty associated with the transition that may be dominant in future, 4 plausible LU scenarios are generated (Table 1). The entire procedure for LU modeling is carried out within the land change modeler framework of the IDRISI model (<https://clarklabs.org/>).

Fig. 3 presents results corresponding to scenario 1 across the three years for which LU is simulated. The LU projection maps for rest of the scenarios along with the percentage of area under various LU categories as obtained for different years under different LU scenarios are presented in Appendix B.

There are two major limitations associated with LU projections (Verburg et al., 2004): first, LU modeling assumes that the transitions that occurred in the past may occur in future making this framework applicable for only short term projections and second, if the ongoing trend in LU categories changes in future due to any reason, the methodology becomes incapable of projecting the change. Due to these limitations, projections of LU for only three time steps ahead in future are carried out in the present work.

Climate projections for a period of 129 years (1971–2099) were procured from the Coupled Model Intercomparison Project (CMIP5) GCM simulations. The projected data was provided by the Coordinated Regional Climate Downscaling Experiment (CORDEX), South Asia group (<http://cccr.tropmet.res.in/cordex/index.jsp>) at daily scale for 2 Representative Concentration Pathway (RCP) climate scenarios, RCP 4.5 (signifies low to medium warming scenario in future) and RCP 8.5 (high warming future scenario). 6 CMIP5 GCMs, as selected by

Chawla and Mujumdar (2015), which provide data corresponding to all the requisite input variables – rainfall (P), maximum temperature ($T_{\max}$), minimum temperature ($T_{\min}$) and wind speed (WS), for the VIC model are considered in the present work (Table C.1). The output variables from all the GCMs are interpolated to a grid resolution of 0.5° in order to match the spatial resolution of the historic/observed data for the study region.

Climate outputs obtained from the GCMs are bias corrected at the grid level with respect to the observed record before being used for hydrologic modeling. Details pertaining to bias correction and performance of GCMs after bias correction may be obtained from Chawla and Mujumdar (2015). Overall model performance, evaluated by comparing monthly climatology and computing correlation metric between model outputs and observed data in the present study, is found to be reasonably good (0.6–0.7 for P and 0.95 for $T_{\max}$ and $T_{\min}$ for all the models) due to which all the 6 models (for 2 climate scenarios) are considered for hydrologic simulations under future scenarios.

To understand the behavior of climate variables under future scenarios (2006 – 2099), mean (*mean*) and different quantile values (5th quantile – q_5 , 50th quantile – q_{50} and 95th quantile – q_{95}) across 6 GCMs are computed for 3 climate variables (P , $T_{\max}$, and $T_{\min}$), results of which are presented as boxplots in Fig. 4. Historic values (1971 – 2005) for different climate variables are also shown in the same plot as red dots. The historic values presented in Fig. 4 are the long-term averages. For instance, historic time series comprises of 35 annual values for a climate variable. Mean and quantiles across these 35 values are obtained and presented as red dots in Fig. 4. Red bars through the mean values are standard deviations of the annual series. Similarly, for future, 12 projections corresponding to 6 GCMs and 2 scenarios are available. Each projection has a series of 94 annual values. Mean and quantiles across these 94 values for the 12 projections are shown as box plots in Fig. 4.

From Fig. 4 it can be inferred that, in general, annual P may decrease across all the three regions in the UGB in future compared to historic/observed values. However, in upstream and midstream regions, a slight increase in the magnitude of low P events may occur in future. Although the decrease in the magnitude of high rainfall events (q_{95}) is noticed, higher variability across the GCMs is observed in this case. Annual $T_{\max}$ and $T_{\min}$ in upstream and midstream regions are found to increase in future time periods. Approximately 2° and 1° rise in temperature is observed for upstream and midstream regions respectively across mean and quantile values. In case of $T_{\max}$ and $T_{\min}$ higher variability amongst the model values is observed for q_{95} , similar to the results obtained for P . This indicates higher uncertainty in the GCMs to simulate extreme events. In general, for upstream and midstream regions, with the decrease in P and increase in annual $T_{\max}$ and $T_{\min}$, more losses are expected from the region that could lead to water deficit conditions in these regions. For the downstream region, mean and q_{50} values of future annual $T_{\max}$ and $T_{\min}$ are observed to be comparable to the historic values while P is noticed to decrease for both the cases. This could lead to the reduction in water availability in the basin. For the q_5 values of the downstream region, all the three variables are observed to decrease. Therefore, the influence on water availability might be minimum in this case as the reduction in P will get balanced by the decrease in the amount of losses from the region.

The climate projections (6 GCMs for 2 climate scenarios) along with 4 LU scenarios thus obtained are used to generate 48 plausible LU-climate combinations, which are fed into the VIC model for the three regions of UGB. Execution of the VIC model is facilitated by the calibration-validation study (over the historic time period).

2.3. Calibration of hydrologic model – hybrid approach

Calibration of the hydrologic models can be carried out either manually or automatically to obtain “best” set of model parameter values. In the present study, for the VIC model, from the set of model

Table 1
Details of the future LU scenarios.

Scenario	Description
1	Changes in scrub forest and crop land areas
2	Change in crop land area
3	Change in urban area
4	Changes in crop land and urban areas

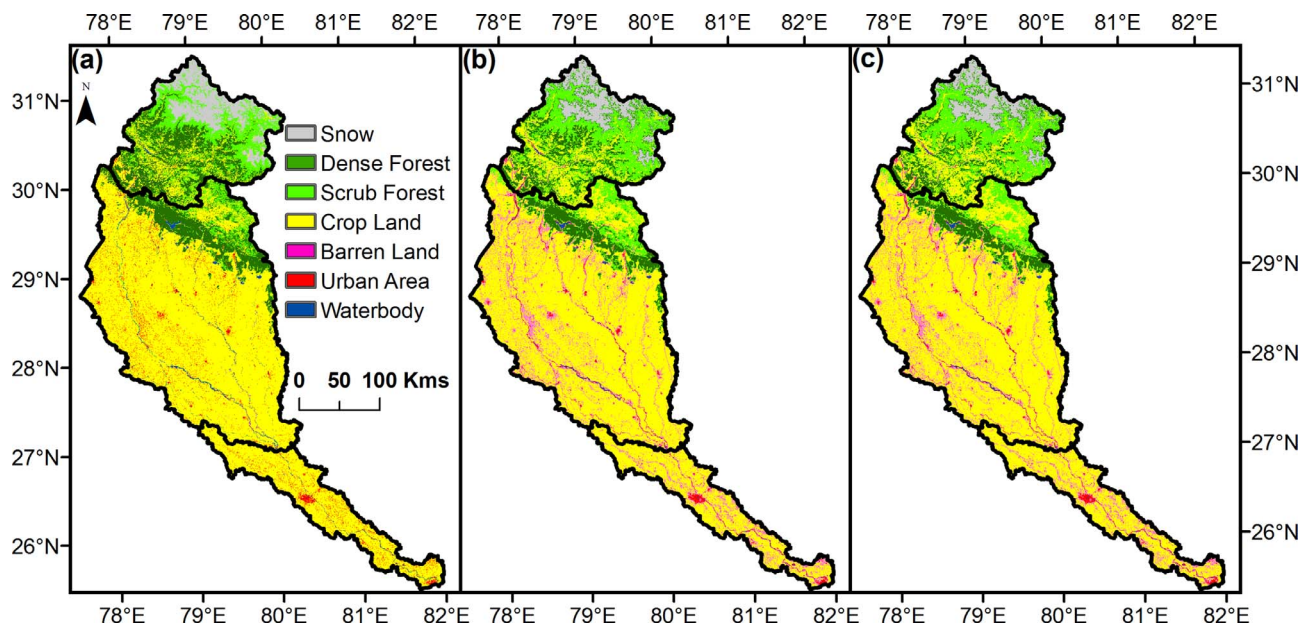


Fig. 3. LU maps of UGB projected for the years (a) 2020; (b) 2030; and (c) 2040 for scenario 1 (changes in scrub forest and crop land areas).

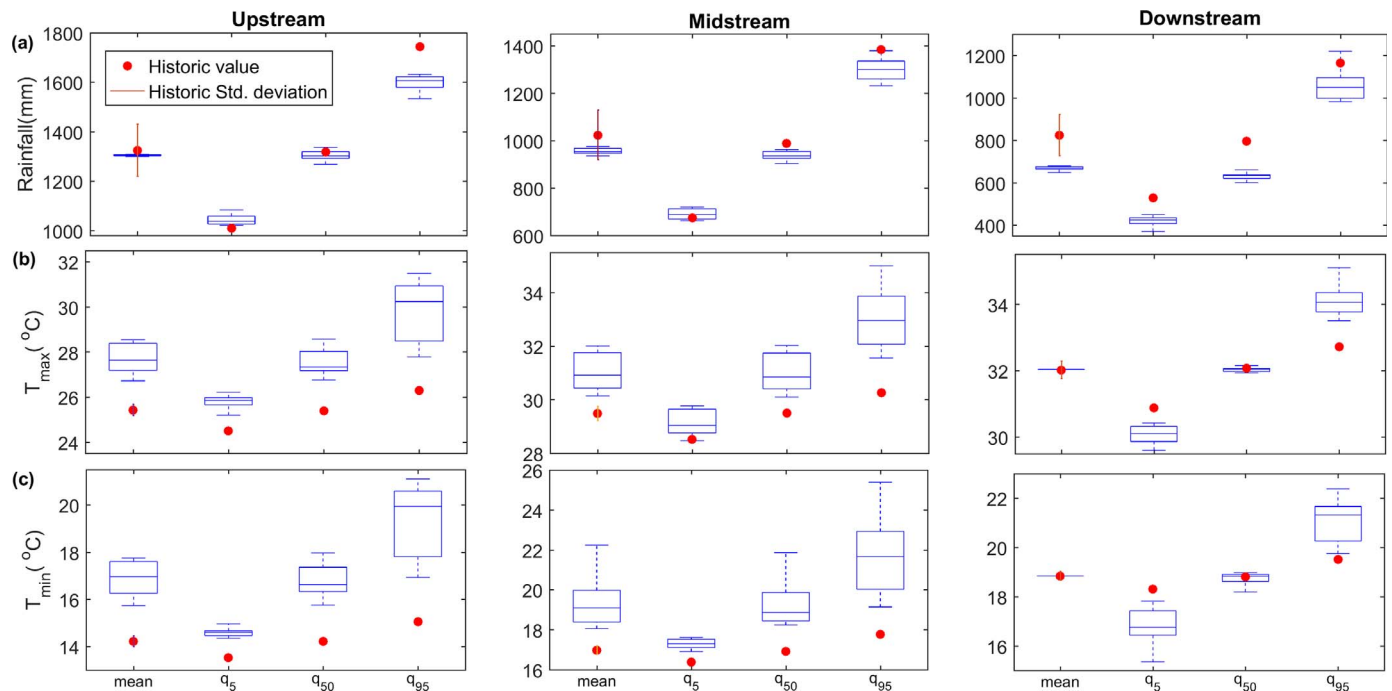


Fig. 4. Comparison between annual (a) rainfall; (b) maximum temperature; and (c) minimum temperature during historic* (1971 – 2005) and future** (2006 – 2099) time periods for upstream, midstream, and downstream regions of the UGB.

* Historic values are represented as red dots in the figure.

** Future values are represented as box plots in the figure.

parameters that need to be determined for model execution, 3 parameters – B , D_s , and W_s – are identified, which require calibration. All the three parameters considered here are dimensionless. B is an infiltration curve parameter, which indirectly influences the surface runoff. In general, B parameter is inversely related to infiltration, i.e., a high value of B parameter indicates low infiltration (more surface runoff) and vice versa. W_s parameter is the fraction of maximum soil moisture where nonlinear baseflow occurs. A higher value of W_s parameter will increase the amount of water content (in the lowest soil layer) required to initiate nonlinear baseflow. As a consequence, there will be high soil moisture storage. D_s parameter regulates the sub surface flow in the

form of baseflow. A high value of D_s results in an increased nonlinear baseflow at lower water content. There are studies reported in the literature (Demaria et al., 2007) where parameters such as soil depth and saturated hydraulic conductivity are also considered in addition to the above-mentioned parameters for calibration. However, for the present study, all the parameters except the three mentioned above are derived from the digital soil map (procured from NBSS & LUP), which limits the number of parameters that require calibration to three. Parameter estimation in the current work is carried out using a hybrid approach, where knowledge of manual calibration is integrated with automatic calibration.

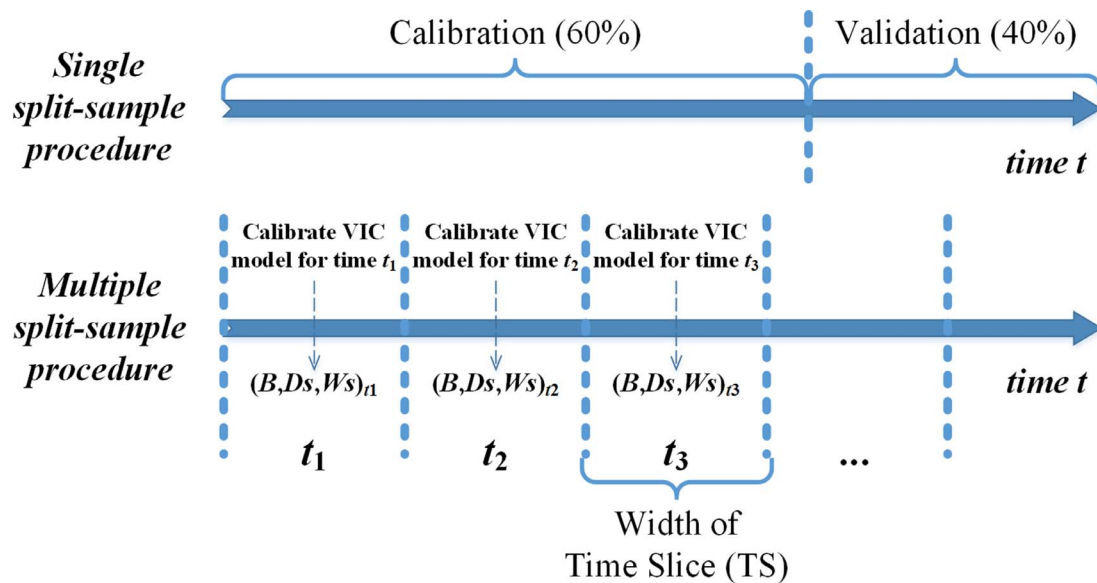


Fig. 5. Construction of different time slices to test stationarity assumption of the hydrologic model.

Automatic calibration of the VIC model is carried out by coupling it with an optimization algorithm, which searches the feasible parameter space (defined by upper and lower bounds of each of the parameters) with an objective of minimizing the error between observed and simulated streamflows. Optimization algorithm in this study is employed by means of an optimization program referred to as Parameter ESTimation (PEST) (Doherty, 2001), which has been used extensively in applications related to water resources (Govender and Everson, 2005; Goegebeur and Pauwels, 2007; Wang and Brubaker, 2015). Through this work, PEST-VIC interface is established for effective implementation of optimization algorithm to obtain “best” parameter estimates of the VIC model for the UGB. Typically, the optimization algorithm carries out search towards attaining global minima (parameters where the objective function is minimized) by initiating the procedure from a random starting point, which plays an important role in achieving the desired output. If this starting point is selected to be far away from optimum, the optimization algorithm can fail in pointing out the “real” best set of parameters. And also, unqualified (outside the feasible parameter space) starting point may increase the computational expense. Hence, in order to address these issues, a hybrid calibration procedure is employed wherein the knowledge gained from manual calibration is utilized in providing an appropriate starting point to the automatic calibration. The outcomes of manual calibration of the VIC model over the UGB are obtained from the analysis carried out by Chawla and Mujumdar (2015). In the present work, the PEST model is executed with an objective function of minimizing the squared sum of errors (SSE) between model simulated streamflow (Q_{sim}) values and observed streamflow (Q_{obs}). Details pertaining to the concept of PEST model can be obtained from Doherty (2001) and Goegebeur and Pauwels (2007).

2.4. Stationarity assumption of the hydrologic model

The VIC model is initially calibrated for the historic time period through a single split-sample approach (using hybrid calibration), wherein data is divided into 60% and 40% for calibration and validation respectively. Information from the associated model parameters is used for projection of streamflows in the future time period. Typically, the model is assumed to be stationary in this case, wherein a fixed set of parameters is used for generating future streamflows without assessing their temporal dynamics. This might lead to unreliable streamflow estimates. Hence, there is a need to assess stationarity assumption of

model parameters to deduce if parameters can be kept constant in the future time period.

In order to investigate model stationarity, multiple split-sample procedure is followed wherein the entire time period available for calibration is divided into several small time slices (TS) and the VIC model is executed independently (through hybrid calibration) over each TS to obtain a series of model parameters through which insights can be gained over temporal variability of the parameters. The time slicing is carried out by considering widths of 1-yr through 5-yr. For example, a 3-yr width time slicing carried out from 1987 to 2004 consists of a total of 6 time periods (1987–89; 1990–92; 1993–95; 1996–98; 1999–2001; 2002–04), within which the VIC model is independently calibrated for each of the time period. Construction of single and multiple split-sample procedures, to test model stationarity is depicted in Fig. 5.

The whole modeling exercise at this stage is aimed to address the research questions – is the model stationary in time and can be directly transferred to future scenarios? Results of this experiment are presented in Section 3.2.

To assess the effect of model stationarity on streamflow simulations, within a particular TS, the model parameter values obtained for the first time period are used to simulate streamflows for rest of the time periods in data series. For instance, for 6 time periods of the 3-yr time slice, model parameters obtained for the first time period are used to execute the VIC model for the other 5 time periods. This is referred to as verification stage, the results of same are presented in Section 3.2.

2.5. Uncertainty quantification

To quantify uncertainty in streamflow projections, a total of 96 simulations are considered – 48 corresponding to changing LU and climate combinations under nonstationary model conditions and other 48 with changing LU and climate but with stationary model conditions. For stationary model condition, parameters obtained from the calibration of the VIC model through single split-sample procedure are used to obtain streamflow projections. However, for obtaining streamflow simulations under nonstationary model conditions, the parameters of calibrated VIC model in the historic time period are projected into future by developing a quantitative relationship between model parameters obtained for 1-yr TS and climate variables, assuming that the relationship will hold good for the future time period. Further details for the same are presented in Section 3.3.

The contribution of different factors to uncertainty in simulated

streamflow is quantified using the ANOVA framework (Von Storch and Zwiens, 2001; Yip et al., 2011; Bosshard et al., 2013). Herein, the difference between simulated value and observed value (Eq. 1) is considered as the input for segregating the uncertainty contribution from different factors. The analysis is carried out using *mean*, q_5 , q_{50} , and q_{95} as summary statistics for streamflow.

$$\Delta X = X_{\text{mod}} - X_{\text{obs}} \quad \forall X = \{\text{mean}, q_5, q_{50}, q_{95}\} \quad (1)$$

where, X_{mod} and X_{obs} respectively represent the model simulated and observed values for a given X .

A multifactor ANOVA model is constructed with GCMs (represented as α , with 6 GCMs represented as, $I = 6$ levels in the ANOVA model), Sce (β , $J = 2$ levels), LU (γ , $K = 4$ levels), MP, stationary or nonstationary (δ , $L = 2$ levels) and IV of the system (ϵ) as the contributing factors (Eq. 2). The interaction between these factors, which represent the nonlinear effect on uncertainty is also considered as a contributing source.

$$\Delta X = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \alpha\beta_{ij} + \alpha\gamma_{ik} + \alpha\delta_{il} + \beta\gamma_{jk} + \beta\delta_{jl} + \gamma\delta_{kl} + \epsilon_{ijkl} \quad (2)$$

The total variance in the streamflow projection is given by the total sum of squares (SS_T) and is decomposed to the sum of squares from contributors and their interactions. Sum of Squares from different sources is represented as SS_f ($\forall f = \{\alpha, \beta, \gamma, \delta, \epsilon\}$). Furthermore, the interaction between different sources is given as SS_n ($\forall n = \{\alpha\beta, \alpha\gamma, \alpha\delta, \beta\gamma, \beta\delta, \gamma\delta\}$). Eq. 3 provides the multifactor ANOVA model considered in this study.

$$SS_T = SS_\alpha + SS_\beta + SS_\gamma + SS_\delta + SS_{\alpha\beta} + SS_{\alpha\gamma} + SS_{\alpha\delta} + SS_{\beta\gamma} + SS_{\beta\delta} + SS_{\gamma\delta} + SS_\epsilon \quad (3)$$

Variance contribution (η^2) of each source is computed as the ratio between SS_f or SS_n and SS_T , for example, $\eta_\alpha^2 = \frac{SS_\alpha}{SS_T}$. Similarly, η^2 for all the factors is calculated and has a value between 0 and 100 percent, where 0 percent means no contribution of a particular factor, while 100 percent means that the given factor is solely responsible for uncertainty in the output.

Further details related to the ANOVA approach can be obtained from Bosshard et al. (2013) and Parajka et al. (2016).

3. Results and discussion

3.1. Calibration and validation of the hydrologic model

The VIC model is initially calibrated and validated through the single split-sample procedure (hybrid approach) for the upstream and midstream regions of the UGB (Section 2.3). In case of the upstream region, 13 years (1987–99) and 6 years (2000–05) of Q_{obs} records are used for calibration and validation respectively at monthly scale. The midstream region is calibrated and validated using 19 years (1977–95) and 10 years (1996–05) of Q_{obs} respectively at monthly scale. Results for the calibration and validation phase are shown in Fig. 6. The model performance is assessed at monthly scale using the statistics of normalized root mean squared error (E_{NRMSE}), coefficient of determination (R^2), Nash-Sutcliffe efficiency (E_{NSE}) and bias (b -where positive sign of b indicates that the model overestimates the streamflow and vice versa); results of the model performance are presented in Table 2.

The peaks are found to be under-estimated consistently during calibration and validation. Since modeling of extremes is not the focus of present work, this misfit is deemed not to be a major concern. The values of the performance measures shown in Table 2 indicate good performance of the hybrid method, particularly in terms of b . However, during validation phase [Fig. 6 (b & d)], the performance of the model deteriorated. The deterioration during validation could be due to two factors. One, the VIC model might have been subjected to over-fitting during the calibration phase and two, the low flows during validation phase are observed to be slightly overestimated (although rest of the features are found to be comparable to that of calibration phase), which could have resulted in poor performance metrics. These results indicate that despite the good performance of the model; caution needs to be exercised while using the model for validation purpose. The contrasting behavior of the VIC model during the two different time periods raises a necessity to understand stationarity of the model with time to determine if model calibrated at certain time period is indeed transferable to the future time period. The following section addresses this issue by analyzing the temporal variability of the VIC model parameters and the influence of chosen time slice for calibration on the model simulations.

3.2. Assessing stationarity of the VIC model

To assess stationarity of the VIC model, the optimum set of

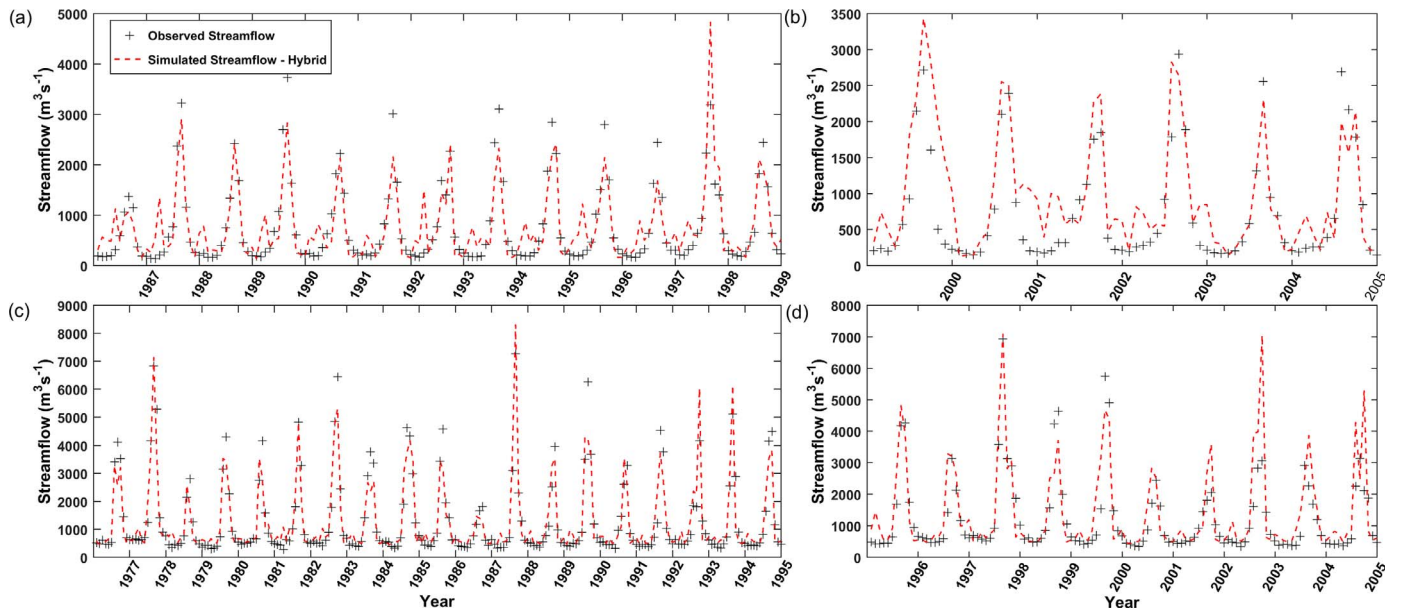
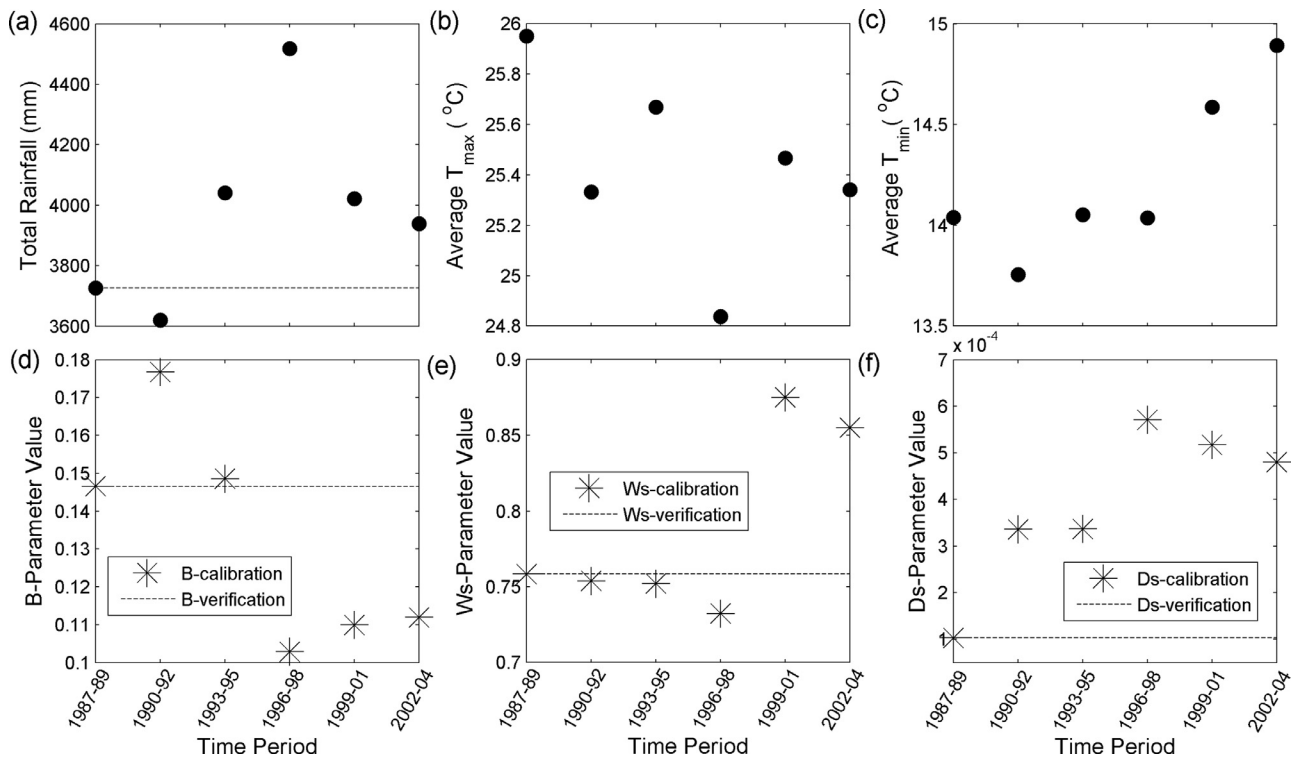


Fig. 6. (a) Calibration results – upstream region; (b) validation results – upstream region; (c) calibration results – midstream region; and (d) validation results – midstream region of the UGB obtained through hybrid approach.

Table 2

Performance measures of the VIC model obtained for the upstream and midstream region during calibration and validation phase.

Region	Value of optimum set of parameters	Calibration				Validation			
		R^2	E_{NRMSE}	E_{NSE}	b (%)	R^2	E_{NRMSE}	E_{NSE}	b (%)
Upstream	$B = 137 \times 10^{-3}$; $Ds = 32 \times 10^{-5}$; $Ws = 63 \times 10^{-2}$	0.77	0.23	0.77	0.6	0.74	0.38	0.61	31
Midstream	$B = 399 \times 10^{-4}$; $Ds = 86 \times 10^{-5}$; $Ws = 633 \times 10^{-3}$	0.88	0.12	0.88	0.5	0.71	0.41	0.59	16

**Fig. 7.** Variations in the (a) total rainfall; (b) maximum temperature; (c) minimum temperature; (d) B; (e) Ws; and (f) Ds model parameters for 3-year time slice for upstream region of the UGB.

parameters obtained in each of the time slicing experiments (Section 2.4) are analyzed for their temporal variability. It is observed that during 1-yr and 2-yr time slicing exercise, model parameters exhibited high variability due to which meaningful interpretation could not be made. From 3-yr TS onwards, temporal variability of the model parameters is observed to be more prominent. Hence, results pertaining to 3-yr TS are used to generalize the temporal behavior of model parameters (4-yr and 5-yr TS have less number of time periods due to which they are not considered for generalization either). Fig. 7 presents results pertaining to this experiment (3-yr TS) for upstream region of the UGB.

Fig. 7 (a-c) present total P , average T_{max} , and average T_{min} for the specified time period respectively and Fig. 7 (d-f) present the temporal variability of B , Ds , and Ws parameter values respectively. Results from the experimental investigation indicate that all the 3 parameters exhibit temporal variability – indicating nonstationarity in the hydrologic model. Therefore, it is now of interest to understand the causal factors for temporal changes in the model parameters. Previous works by Demaria et al. (2007) and Troy et al. (2008) have shown VIC parameters to be sensitive to climate. In this paper, a non-linear Spearman rank correlation coefficient is used to determine the dependence between model parameters and climate indicators, results for which are presented in Appendix D (Table D.1). It is observed that B and Ds parameters are strongly correlated to P while Ws parameter is highly

correlated with T_{max} and T_{min} . The relationship between model parameters and climate variables is also shown in Fig. 7. In general, across any two time periods, a decrease in P is accompanied by an increase in B parameter value, which indicates the reduction in infiltration of water into the soil. A drop in the value of T_{max} and T_{min} may cause the decrease in losses from the system, consequently, Ws parameter value may decrease or vice versa. The decrease in the value of Ws parameter is linked with an increase in Ds parameter value demonstrating an increase in baseflow contribution (at low soil moisture content) towards total runoff. Overall, it can be inferred that B parameter is indirectly related to P , whereas T_{max} and T_{min} have a direct relationship with Ws parameter. Ds parameter complements the effect of variations in B and Ws parameters. Similar behavior in model parameters with respect to the change in climate indicators is demonstrated by the midstream region of the UGB (Appendix E, Fig. E.1).

Further, to assess the effect of the nonstationary VIC model on streamflow simulations, bias (b) is estimated between Q_{sim} for calibration and verification phase (Section 2.4 for further information) for each time period. Results of the analysis are presented in Fig. 8. If there is no effect of model parameters on streamflow simulations, then b should be approximately equal to zero.

The analysis indicates that exclusive changes either in B or Ds parameters will have a proportional effect over streamflow. Moreover,

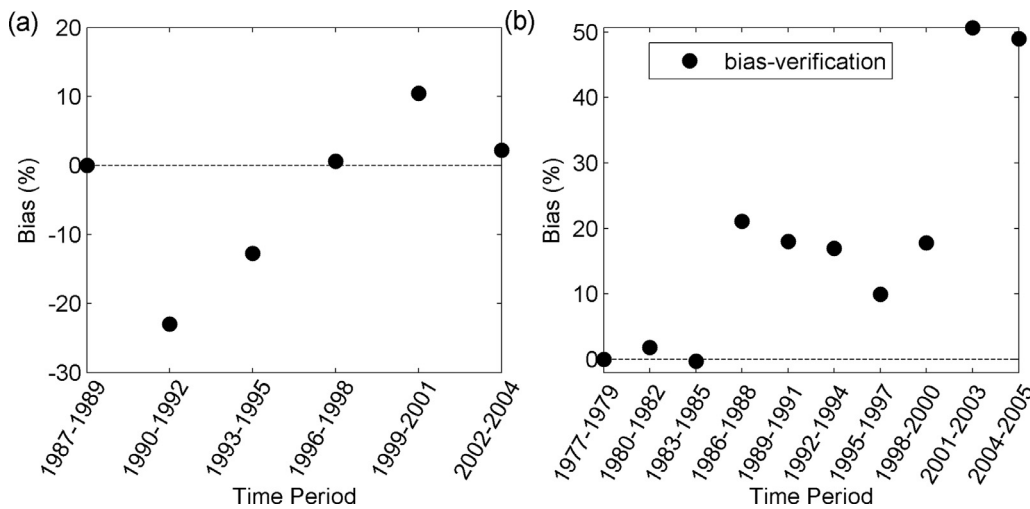


Fig. 8. Bias obtained by comparing streamflow simulated with a constant set of model parameters corresponding to first time period with respect to simulations obtained with varying model parameters for (a) upstream and (b) midstream regions of the UGB.

a simultaneous increase in both B and D_s parameters is observed to result in significant increase in streamflow. It is also observed that an increase in B parameter along with a decrease in W_s parameter leads to increase in streamflow and vice versa. However, the extent to which overestimation or underestimation of streamflow occurs depends on the amount by which each of the parameter value changes. Therefore, it can be concluded that assuming the hydrologic model to be stationary may have a significant effect on streamflow projections. Consequently, for assessing the contribution of different factors to uncertainty in streamflow projection, nonstationarity should be considered.

It is now important to assess if the width of TS has any effect on the dynamics of streamflow simulations so as to comment if the inferences drawn above for the 3-yr time slice experiment can be applied to other TS experiments. This inherently provides us with an insight about uncertainty due to the choice of TS during calibration. The objective is

addressed by initially executing the VIC model under all the TS widths along with complete time period (Upstream – 1987–05; Midstream – 1977–05) and the resulting Q_{sim} is compared with Q_{obs} using E_{NSE} and b measures. The corresponding results are presented in Fig. 9. The performance measures indicate that all the TS except complete time period have well simulated the streamflows with comparable accuracies in both upstream and midstream regions. Consideration of complete time period resulted in poor simulations in both the regions. This could be due to overestimation of flows during model validation phase (Section 3.1). It can be inferred from the results that changing TS width has minimal effect on the model through which it can be said that uncertainty due to the choice of TS is negligible and can be ignored in the current work.

From this section, it is established that model parameters indeed vary over time with noticeable effect over streamflow simulations. Hence, it can be concluded that the VIC model is not stationary,

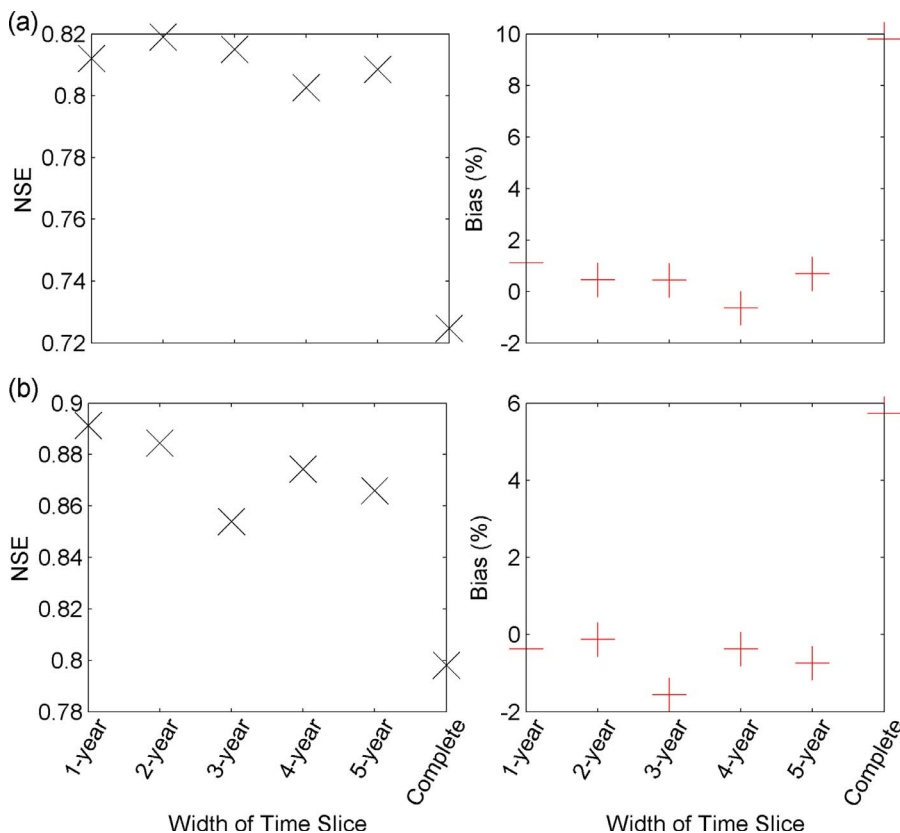


Fig. 9. Performance measures between observed streamflow and simulated streamflow for different widths of time slices for (a) upstream and (b) midstream regions of the UGB.

consequently not directly transferable to future scenarios i.e., calibrated model parameters obtained for the past cannot be applied directly to future conditions. Since it is evident from previous analysis that the model parameters are influenced by climate variables, a regression mechanism is set up for the historic data by which model parameters for the future time periods are estimated.

3.3. Model parameters for future time periods

The parameters of calibrated VIC model in the historic time period are projected into future by developing a quantitative relationship between parameters and climate variables (assuming that the relationship thus established will hold good for the future time period). However, the regression model to be setup is rather complicated due to multi-dimensional nature of both predictor (3 climate variables, P , $T_{\max}$, and $T_{\min}$) and predictand (3 model parameters, B , Ws , and Ds) datasets. Under such circumstances, Dattalo (2013) suggested that if the predictand variables are poorly correlated among themselves (correlation, $\rho < 0.2$) then each of these variables can be modeled separately with respect to predictor variables. In the present work, the model parameters are observed to be uncorrelated, due to which each one of the parameters is individually regressed with predictors. For establishing the relationship, Support Vector Regression (SVR) algorithm is employed wherein model parameters (predictors) and climate variables (predictands) corresponding to 1-yr width TS are considered, which resulted in 19 and 29 number of datasets available in the upstream and midstream regions respectively. These datasets are divided into 70% and 30% respectively for training and validation of relationship.

SVR technique, initially developed by Cortes and Vapnik (1995), has been widely applied in the past few decades for classification and regression analysis, owing to its ability in solving large-scale complex problems (Tripathi et al., 2006). It is based on a general idea of mapping dependent variables nonlinearly to the high dimensional independent variables. Brief description of the SVR algorithm is provided in Appendix F. Further details can be obtained from Cortes and Vapnik (1995); Smola (1996); Smola et al. (1998); Hsu et al. (2003); Tripathi et al. (2006) and Ghosh (2010). Results corresponding to training and validation of SVR for the upstream and the midstream regions of the UGB are provided in terms of the correlation coefficient in Table 3.

The results indicate that in general, SVR has modeled parameters in the upstream and midstream regions with a reasonable accuracy despite slight inconsistency in validating Ds parameter. At the end of this modeling exercise, each region contains 3 trained SVR models corresponding to the B , Ds , and Ws parameters. These models are fed with future projections of the 3 climate variables corresponding to the 6 GCMs and 2 climate scenarios so as to obtain projected values of model parameters.

3.4. Hydrologic impacts of future land use and climate change

The VIC model with projected model parameters (nonstationary model condition) is executed in future time periods across 48 climate and LU scenarios to obtain future Q_{sim} for the UGB. Further, the VIC model is also run for the same set of LU and climate projections with model parameters obtained during the single split-sample calibration procedure (i.e., stationary model condition) and the resulting streamflows act as a baseline. Fig. 10 presents boxplots of summary statistics

Table 3
Correlation values obtained during training and validation of the SVR model.

Region	Training			Validation		
	B	Ds	Ws	B	Ds	Ws
Upstream	0.71	0.64	0.99	0.76	0.42	0.86
Midstream	0.86	0.53	0.98	0.83	0.26	0.53

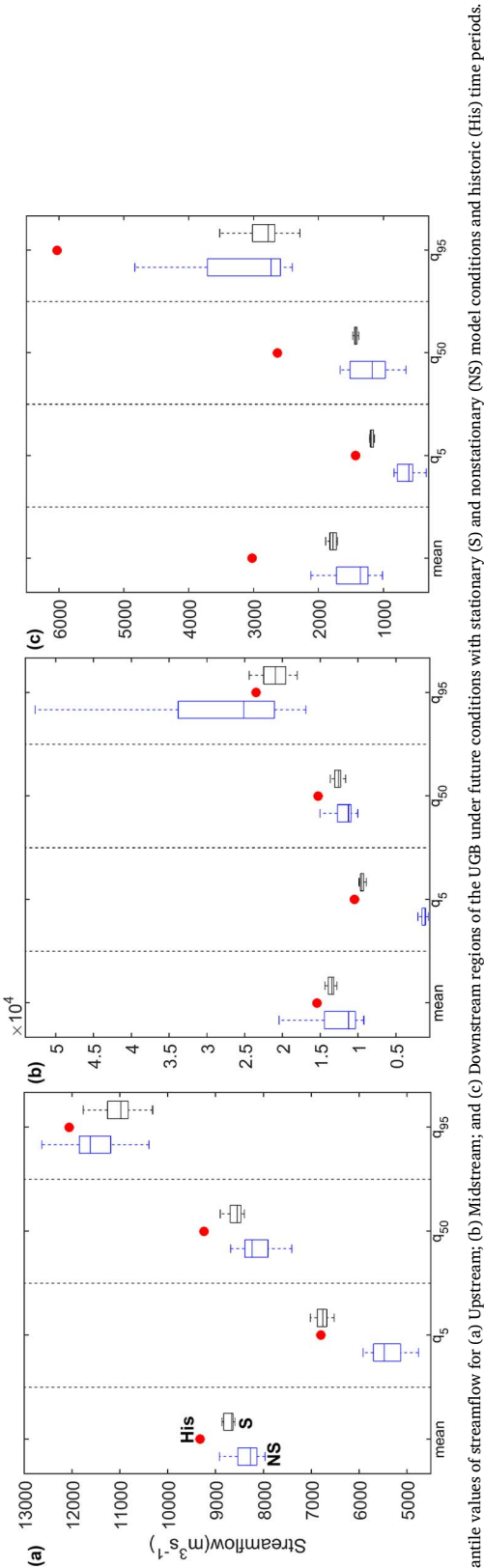


Fig. 10. Annual mean and quantile values of streamflow for (a) Upstream; (b) Midstream; and (c) Downstream regions of the UGB under future conditions with stationary (S) and nonstationary (NS) model conditions and historic (His) time periods.

for the streamflow projections obtained for 48 projections under both nonstationary and stationary conditions along with historic observations.

Streamflow is noticed to decrease in future for both – nonstationary and stationary conditions. This is due to decrease in rainfall and increase in temperature obtained for future projections across all the GCMs (Fig. 4). Further, amongst the two conditions, streamflow is noticed to be significantly low for the nonstationary model. This difference is attributed to contrast in model parameters (B , W_s , and D_s) used in two conditions. Under the stationary condition, model parameters used for simulations are basically tuned for historic climate thus being insensitive to future climate projections. Due to strong dependency of model parameters with climate conditions (Section 3.2), parameters are misrepresented in stationary condition resulting in unrealistically higher future streamflows. This issue is effectively addressed by implementing nonstationary VIC model wherein model parameters for future time period vary according to prevalent climate resulting in lower streamflow projections.

For instance, in the upstream region, under the nonstationary condition, average values of W_s and B across all the GCMs and Sce are found to lie between 0.79 to 0.83 and 0.104 to 0.121 respectively, whereas 0.63 and 0.137 respectively, are the values considered in the stationary condition. This resulted in higher streamflow for the latter condition. For low flow case (q_5) in upstream and midstream regions, streamflow values under stationary conditions are found to be comparable to the historic values. This could be due to the insignificant change in the low rainfall events in the two regions (Fig. 4). Further, it indicates that the influence of the increase in temperature is not reflected in streamflow projections obtained using stationary hydrologic model condition. However, significantly lower streamflow is obtained for the nonstationary condition under the same case, which could be due to increase in W_s parameter values as a result of an increase in temperature. In addition to this, uncertainty in streamflow values for the nonstationary case is observed to be higher compared to the stationary case. This could be due to variability in the model parameters and consequently in streamflow projections across different GCMs and Sce. For high flows (q_{95}), uncertainty is observed to be maximum as reflected through widest box plot amongst all the cases. Although most of the values are either below the historic values or lie towards the lower end, they are exceeding the stationary values in some cases. A mismatch between the parameters obtained for high rainfall events could be the cause for obtaining these varying values. This implies that the methodology should be exercised with caution for high rainfall events. A separate relationship in such situation might reduce the uncertainty in simulations.

3.5. Uncertainty contribution from different sources

As described in Section 2.5, uncertainty in the streamflow projections is decomposed into individual components (GCMs, Sce, LU, MP and IV) using the ANOVA approach. Results for three regions of UGB are presented in Fig. 11.

GCMs and MP assumption of nonstationary and stationary are observed to be the primary source of uncertainty across all the three regions and for most of the cases. This could be due to the fact that there is a noteworthy difference in the streamflow projections obtained for different LU and climate scenarios under stationary and nonstationary conditions and also within each of these conditions. q_{95} of midstream and downstream regions exhibited significant variability for both nonstationary and stationary model conditions. Therefore, GCMs contribution to q_{95} case is observed to be less (in comparison to the mean case). Further, uncertainty contribution from MP towards change in q_5 of midstream and downstream regions is noticed to be very high (96% and 82% respectively). This is attributed to significant difference between the low flows obtained under the two conditions for midstream and downstream regions. Interactions between GCMs – Sce; GCMs – MP and Sce – MP are found to be the next significant contributor with contribution ranging between 30 – 50% across all the cases (except q_5 case of midstream and downstream regions). This indicates that GCMs, Sce and model assumptions should be considered together for future assessment of water resources within the uncertainty framework. In addition to this, contribution from LU and IV is found to be less but not negligible. From this analysis, it can be inferred that consideration of hydrologic model to be stationary or nonstationary might be a significant source of uncertainty in future streamflow projections. To understand the influence of other factors on uncertainty a separate set of analysis is performed where streamflow projections only from nonstationary model conditions are considered. Result pertaining to the same are presented in Fig. 12.

In the nonstationary case, GCMs and Sce are observed to be the dominant contributor to uncertainty in streamflow across all the cases. This is expected due to variability in the streamflow simulations under nonstationary conditions for different models and scenarios. For upstream and midstream regions, the contribution from LU is also noticeable in all the cases. However, this contribution is not observed for the downstream region. This could be due to the lesser contributing area in the downstream region (least amongst the three sub-basins). The effect of the amount of contributing area is also seen in the results for the other two regions wherein midstream region having maximum basin area has highest LU contribution towards uncertainty, which reduces for the upstream region.

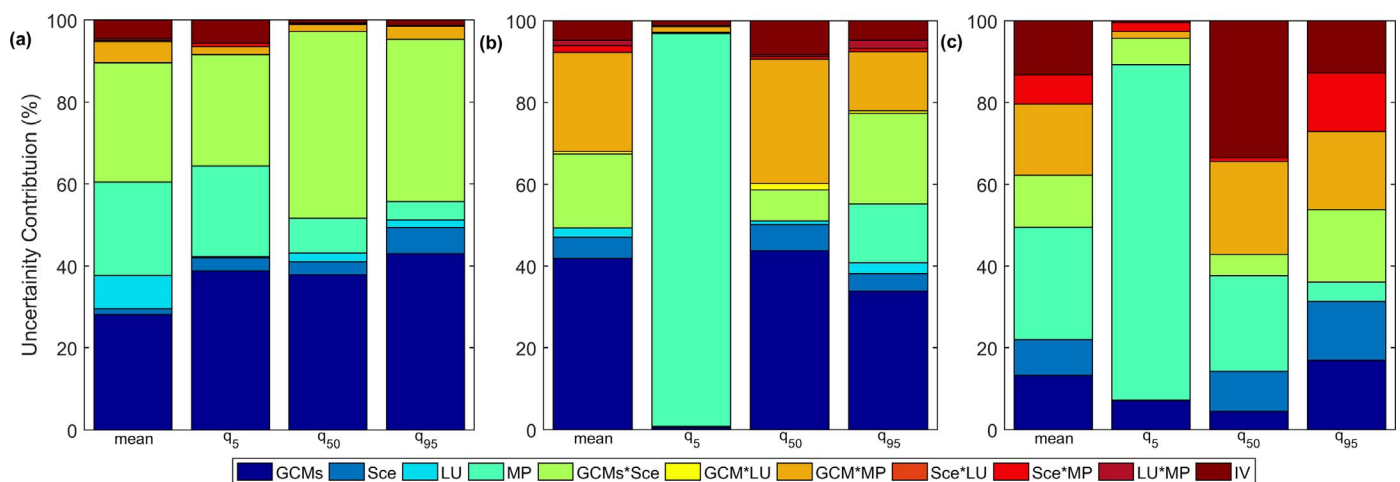


Fig. 11. Contribution of different factors to uncertainty of annual streamflow projections (change in mean, 5th quantile, 50th quantile and 95th quantile) for (a) Upstream; (b) Midstream; and (c) Downstream regions of the UGB under both stationary and nonstationary model conditions.

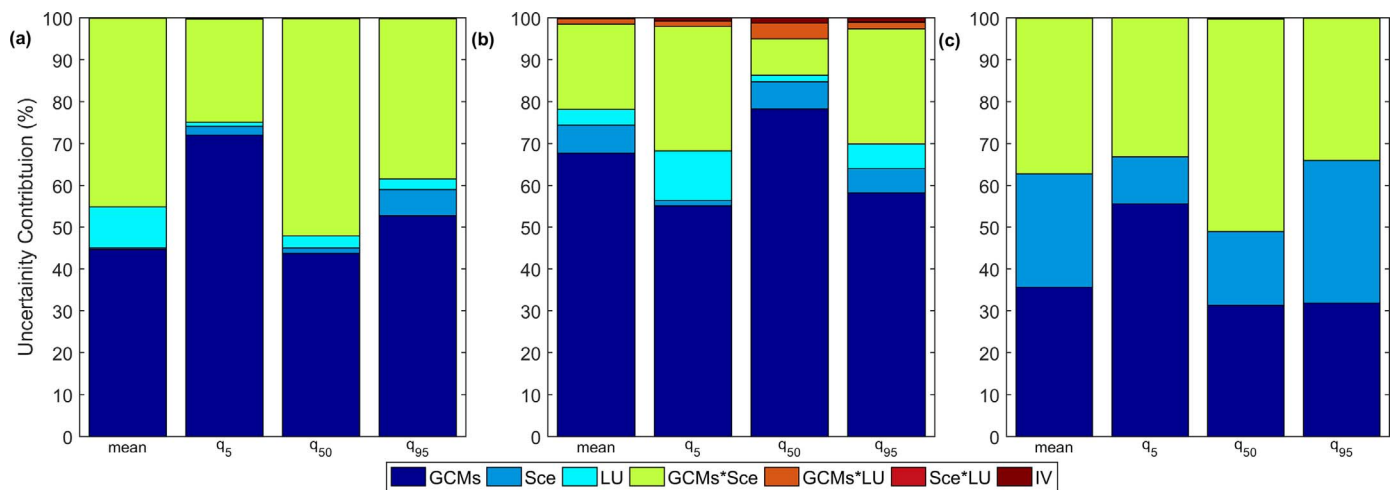


Fig. 12. Contribution of different sources to uncertainty of annual streamflow projections (change in Mean, 5th quantile, 50th quantile and 95th quantile) obtained under nonstationary model condition for (a) Upstream; (b) Midstream; and (c) Downstream regions of the UGB.

4. Summary and conclusions

This paper sought to address two main objectives: first, assessing the influence of model stationarity on future streamflow simulations, and second, quantify the contribution of GCMs, emission scenarios, LU, model parameters and internal variability of the hydrologic model to uncertainty in streamflow projections. A semi-distributed VIC hydrologic model combined with the PEST optimization algorithm is used to carry out the analysis. Calibration of the VIC model is carried out through a hybrid approach, which involves integrating the manual calibration with that of automatic calibration (using the PEST model).

Through time slicing experiment, it is noticed that the model parameters exhibit temporal variability, thus leading to the necessity of using a nonstationary model for streamflow projections. Streamflow is observed to decline under future LU and climate conditions. Further, low flows are observed to be critically low, which may become a matter of concern for assessment of future water availability. Upon segregating the contribution of different factors to uncertainty in streamflow projections, it is observed that GCMs and model assumption of stationary and nonstationary conditions are the major source of uncertainty. Within the nonstationary case, GCMs are found to be the dominant contributor to the uncertainty in streamflow projections. It is also revealed that the nonlinear interactions between GCMs and scenarios are important for uncertainty quantification in streamflow projections. Streamflow is noticed to be sensitive to subtle changes in the LU.

The key aspect of this paper is that the hydrologic models cannot be assumed to be stationary for impact assessment studies. Instead, it can

be the significant source of uncertainty in the model output. In addition to this, future LU scenarios can also contribute towards uncertainty. Although the results presented in this paper are not directly applicable to another catchment with different hydrological properties, the methodology presented is general and can be performed independently of the study area. This study will be helpful for assessing future impacts of LU and climate change on streamflow within the uncertainty framework.

4.1. Limitations and future scope

Analysis presented in this paper is subjected to a few limitations: (a) segregation results obtained are limited to the GCMs selected for the study, (b) uncertainty in streamflow simulations due to model structure is not considered, (c) irrigation and groundwater extraction, which are dominant phenomenon in the region (Misra, 2011; Madhusoodhanan et al., 2016), may also be a source of uncertainty, which are not included in the present model set-up, (d) due to the drawbacks associated with LU modelling, LU could be projected only for a short time in future (2040), and (e) optimization of the hydrologic model is carried out based on a single objective function. The multi-objective optimization of the VIC model with evapotranspiration and soil moisture might improve the results and should be attempted in future work. In addition to the above-mentioned limitations, care should be exercised while using the hydrologic model for simulating extreme rainfall events, as it is observed that the VIC model doesn't capture the extremes well in the present case study (Section 3.1).

Appendix A

Validation results of the LU model

Fig. A.1 along with Table A.1 present the area under different LU categoried for observed and simulated LU map of the year 2011.

The accuracy of the simulated map of 2011 is measured using kappa index of agreement (KIA), originally developed by Pontius (2000). Value of KIA may lie between 0 to 1 where 1 indicates perfect agreement between simulated and observed images and 0 indicates that the agreement is as good as expected by chance. In this paper, three variants of KIA (Pontius, 2000) are used (Table A.2) to measure different characteristics pertaining to simulation capability of the LU model.

The quantitative KIA metrics indicate that the LU model has simulated the quantity of correctly classified pixels with better accuracy than spatial accuracy. However, overall capability of the model to simulate change (κ_{standard}) is observed to be reasonably good.

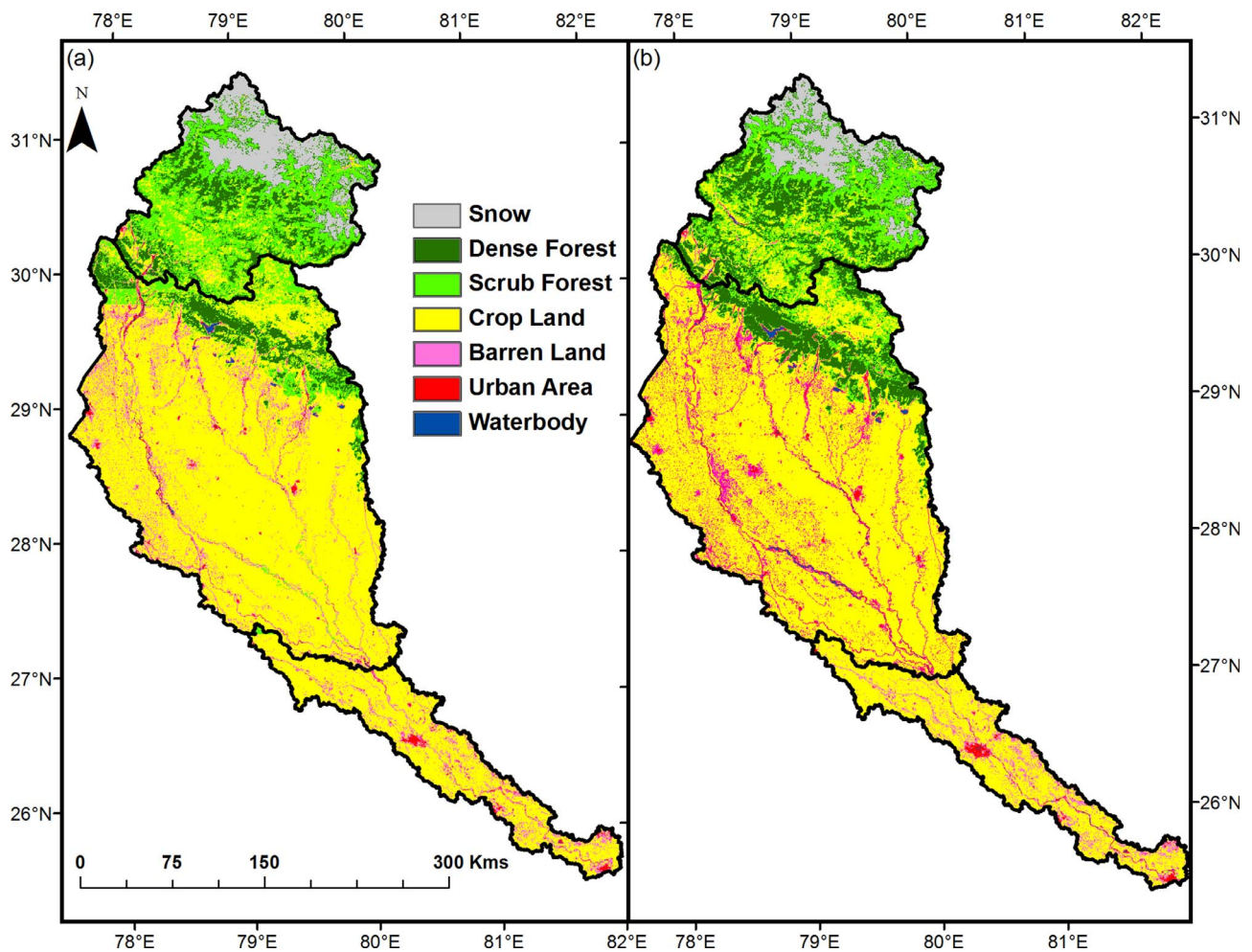


Fig. A.1. Land use maps of the UGB for the year 2011 (a) simulated using the LU model; and (b) observed.

Table A.1

Proportion of areas (in %) under different LU categories for historic time periods.

LU category	2011 – simulated	2011 – observed
Snow	6.55	5.49
Dense Forest	11.58	14.83
Scrub Forest	13.11	8.99
Crop Land	64.80	66.18
Barren Land	0.39	0.19
Urban Area	2.63	3.23
Waterbody	1.04	1.12

Table A.2

Value of Kappa Index of Agreement obtained for simulated and observed LU images for the year 2011.

KIA	Description	Value
κ_{location}	Measure of the spatial accuracy due to correct assignment of pixel values	0.74
κ_{quantity}	Measure of simulation's ability to accurately specify quantity of correctly classified pixels	0.84
κ_{standard}	Observed proportion of pixels that are correctly classified versus the proportion of pixels correctly classified by chance	0.67

Appendix B

Future land use (LU) projections corresponding to different scenarios

From scenario 1 (Fig. B.1 and Table B.1), where changes in scrub forest and crop land areas are modeled, a slight increase in both the categories can be observed from 2020 through 2040. This increase is noticed to be at the expense of dense forest category. In case of scenario 2, which focuses on crop land changes, an increase in this category is noticed for 2020 and 2030 at the expense of barren land and scrub forest categories. However, this scenario witnessed a slight unexpected decrease in crop land area during 2040, which is compensated with an increase in area under scrub forest. This feature, although negligible, could be viewed as a modeling inconsistency. Scenario 3 (Fig. B.2), which models changes in urban area, witnessed urban area expansion from 2020 to 2040 at the cost of scrub forest and crop land areas. This can be considered as an increase in the size of existing urban areas in the region in the coming years due to population growth. Lastly, in scenario 4 (Fig. B.3), where changes in crop land and urban areas are modeled through time, increase in crop land area is observed to have replaced scrub forests from 2020 to 2040 while urban area remained constant (after an initial increase in 2020).

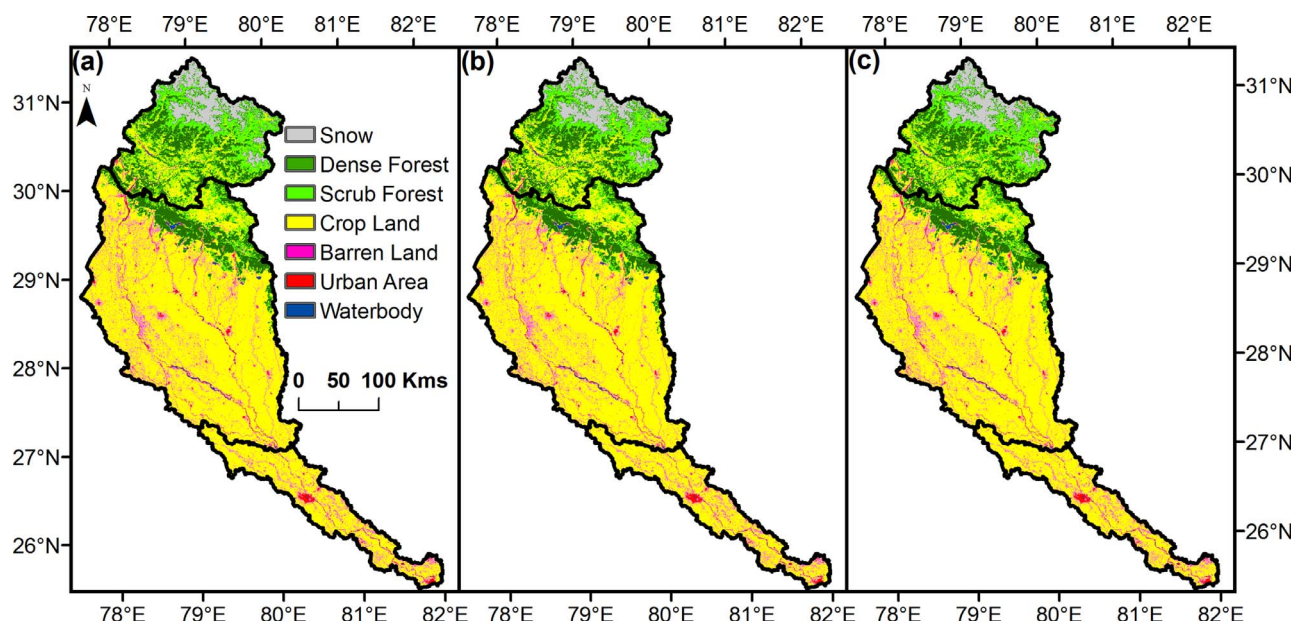


Fig. B.1. LU maps of UGB projected for the years (a) 2020; (b) 2030; and (c) 2040 for scenario 2 (change in crop land area alone).

Table B.1

Proportion of areas (in %) under different LU categories for future scenarios.

LU category	2020				2030				2040			
	Sce-1	Sce-2	Sce-3	Sce-4	Sce-1	Sce-2	Sce-3	Sce-4	Sce-1	Sce-2	Sce-3	Sce-4
Snow*	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6
Dense Forest	13.2	14.8	14.8	14.8	11.6	14.8	14.8	14.8	12.8	14.8	14.8	14.8
Scrub Forest	10.0	8.4	8.9	7.9	10.9	7.8	8.9	6.9	9.2	8.9	7.1	8.5
Crop Land	66.9	66.9	65.1	67.3	67.6	67.6	64.1	68.4	68.0	66.3	65.1	69.4
Barren Land	0.2	0.1	0.2	0.1	0.2	0.0	0.2	0.0	0.2	0.0	0.2	0.0
Urban Area	3.2	3.2	4.4	3.3	3.2	3.2	5.4	3.3	3.2	3.2	6.2	3.3
Waterbody*	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1

* area under snow and water body are kept constant during future projections

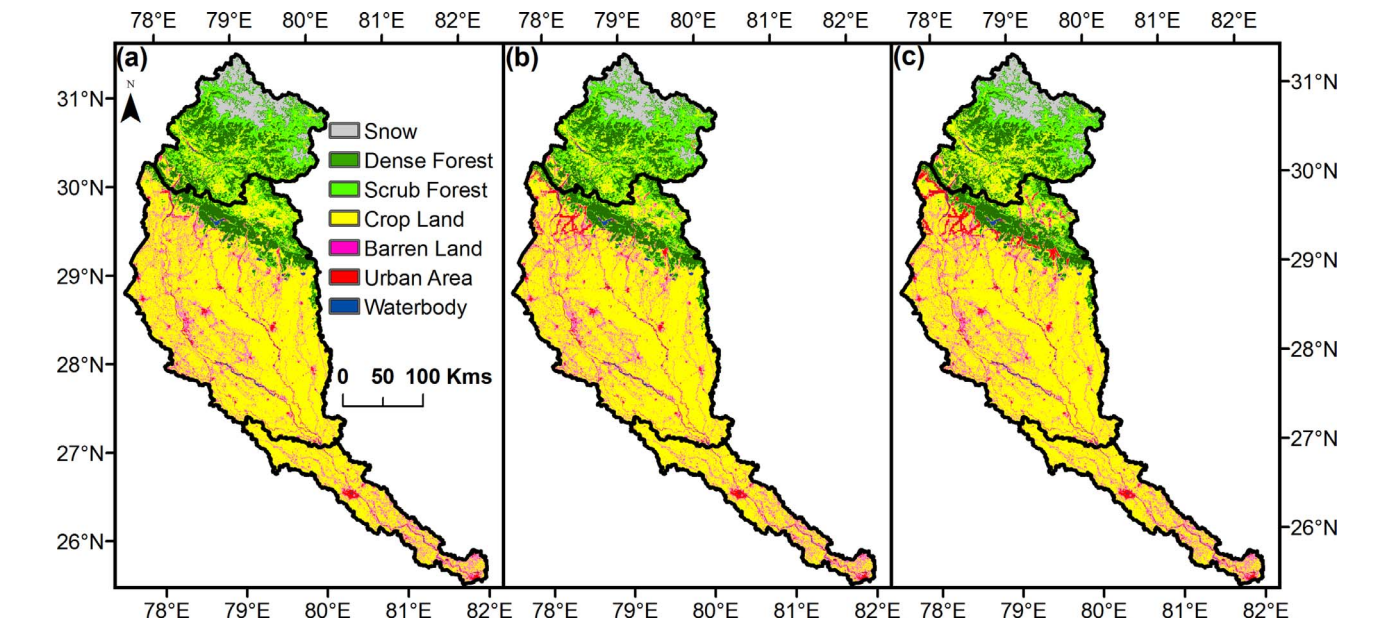


Fig. B.2. LU maps of UGB projected for the years (a) 2020; (b) 2030; and (c) 2040 for scenario 3 (change in urban area only).

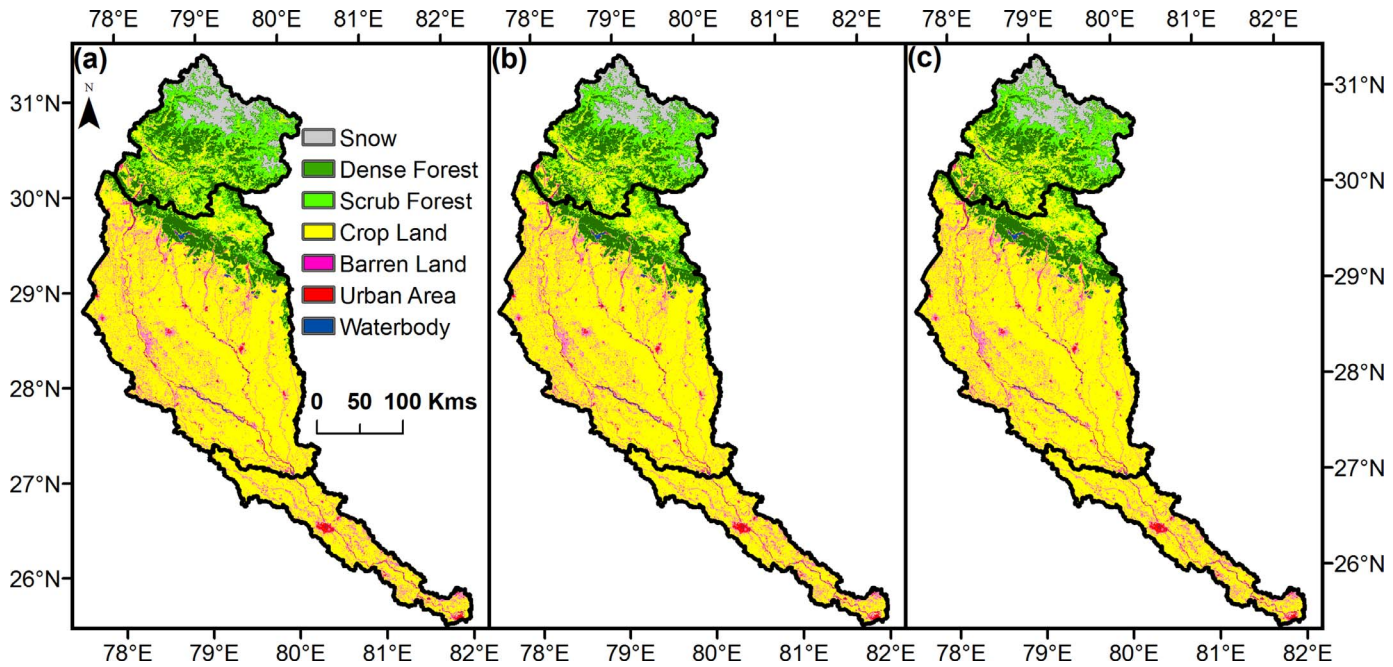


Fig. B.3. LU maps of UGB projected for the years (a) 2020; (b) 2030; and (c) 2040 for scenario 4 (changes in crop land and urban areas).

Appendix C

List of GCMs considered in the present work.

Table C.1		
CMIP5 GCMs (obtained from the CORDEX project) used in the present study (reproduced from Chawla and Mujumdar, 2015).		
GCM	Model Center	Abbreviation
ACCESS1.0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	ACC
CCSM4	National Center for Atmospheric Research	CCS
CNRM-CM5	Centre National de Recherches Meteorologiques	CNR
GFDL-CM3	Geophysical Fluid Dynamics Laboratory, NOAA	GFD
MPI-ESM-LR	Max Planck Institute for Meteorology	MPI
NorESM1-M	Norwegian Climate Centre	NOR

Appendix D

Table D.1

Spearman rank correlation coefficient between the VIC model parameters and the climate variables for the upstream and the midstream regions of the UGB.

Model Parameter	Climate Variable	Upstream		Midstream	
		ρ	p-value	ρ	p-value
<i>B</i>	<i>P</i>	−0.66	0.17	−0.65	0.05
<i>Ds</i>	<i>P</i>	0.77	0.10	0.44	0.20
<i>Ws</i>	<i>P</i>	−0.43	0.42	−0.35	0.33
<i>B</i>	<i>T_{max}</i>	0.31	0.56	0.36	0.31
<i>Ds</i>	<i>T_{max}</i>	−0.6	0.24	−0.28	0.43
<i>Ws</i>	<i>T_{max}</i>	0.37	0.50	0.71	0.03
<i>B</i>	<i>T_{min}</i>	−0.31	0.56	−0.03	0.95
<i>Ds</i>	<i>T_{min}</i>	0.26	0.66	0.13	0.73
<i>Ws</i>	<i>T_{min}</i>	0.66	0.17	0.39	0.26

Appendix E

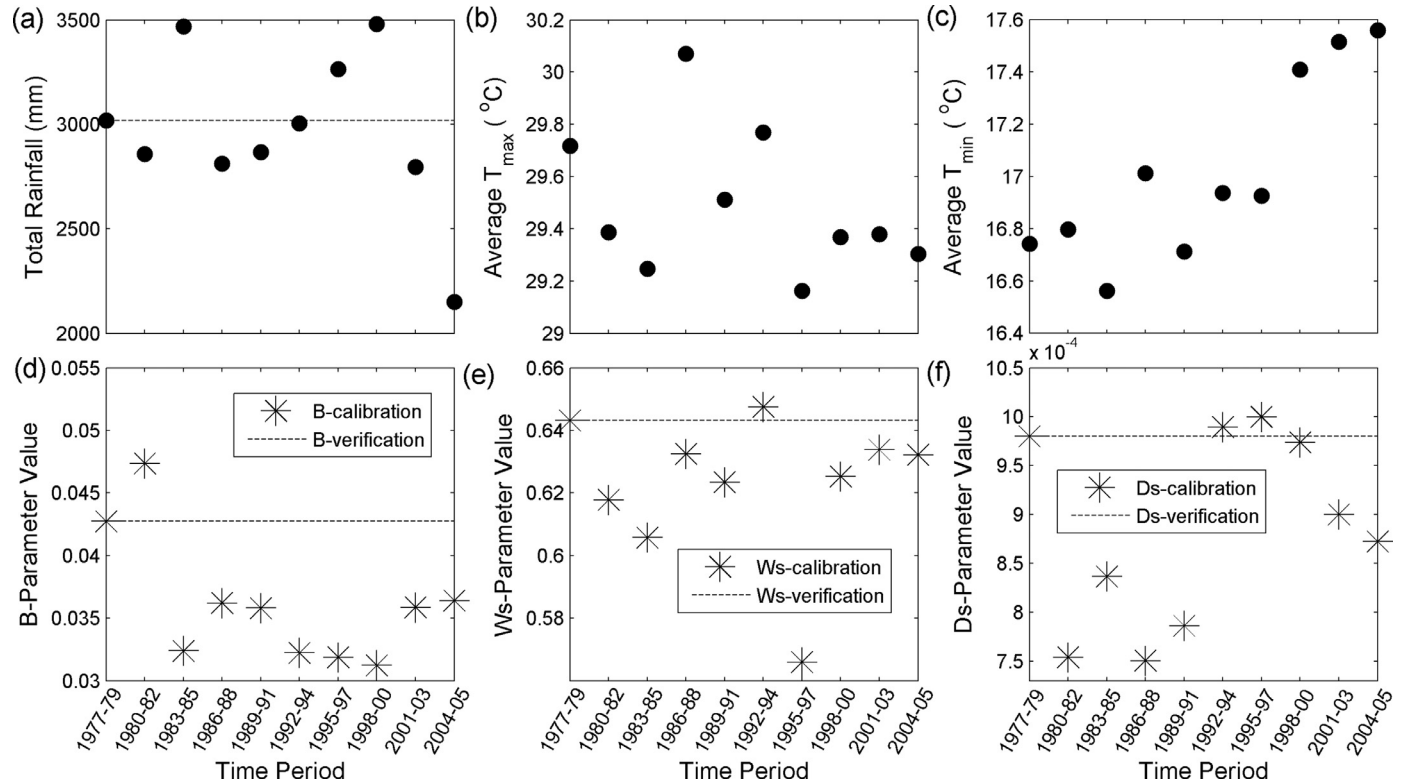


Fig. E.1. Variations in the (a) total rainfall; (b) maximum temperature; (c) minimum temperature; (d) B; (e) Ws; and (f) Ds model parameters for 3-year time slice for midstream region of the UGB.

Appendix F

Quantitative relationship between model parameters and climate variables is established through Support Vector Regression (SVR) algorithm. It is based on a general idea of mapping dependent variables nonlinearly to the high dimensional independent variables. The formulation of SVR is provided below.

Consider a training sample of N datasets of predictors (x) and predictand (y) $\{(x_i, y_i), i = 1, 2, \dots, N\}$, where x_i is the i^{th} vector containing n number of predictor variables i.e. $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]$. The structure of the SVR is given by the following equation.

$$\hat{y} = \sum_{i=1}^N w_i \times K(x_i, x) + b \quad (\text{F.1})$$

where, w_i are the adjustable weights; b is the bias; $\hat{y}$ is an estimate of y and $K(\cdot)$ is a kernel function. The Kernel function transforms the training data into high dimensional space so as to model nonlinear dependencies between predictors and predictand. In the present work, radial basis function (RBF) is used as a kernel function (Eq. F.2).

$$K(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right) \quad (\text{F.2})$$

where, σ is the width of the RBF kernel. SVR systematically adjusts weights and bias with an objective of minimizing the error between y and $\hat{y}$.

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